Public Interest Energy Research (PIER) Program

White Paper

IMPACTS OF CLIMATE CHANGE ON SAN FRANCISCO BAY AREA RESIDENTIAL ELECTRICITY CONSUMPTION: EVIDENCE FROM BILLING DATA

A White Paper from the California Energy Commission's California Climate Change Center

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PREFACE

The California Energy Commission's Public Interest Energy Research (PIER) Program supports public interest energy research and development that will help improve the quality of life in California by bringing environmentally safe, affordable, and reliable energy services and products to the marketplace.

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In 2003, the California Energy Commission's PIER Program established the California Climate Change Center to document climate change research relevant to the states. This center is a virtual organization with core research activities at Scripps Institution of Oceanography and the University of California, Berkeley, complemented by efforts at other research institutions.

For more information on the PIER Program, please visit the Energy Commission's website http://www.energy.ca.gov/research/index.html or contract the Energy Commission at (916) 327-1551.

ABSTRACT

This study simulates the impacts of higher temperatures resulting from anthropogenic climate change on residential electricity consumption for the nine San Francisco Bay Area counties (Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Solano, and Sonoma). Flexible temperature response functions are estimated by climate zone, which allows for differential effects of days with different meant temperatures on households' electricity consumption. The estimation uses a comprehensive household-level data set of billing data for Pacific Gas and Electric Company). The results suggest that the temperature response varies greatly across climate zones. Simulation results using three downscaled climate models suggest that for constant population the total demand for the households that were considered may increase by between 1 to 4 percent by the end of the century. The study further simulates the impacts of higher electricity prices and different scenarios of population growth.

Keywords: Climate change, electricity, impacts, residential sector, simulation

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1.0 Introduction

Forecasts of electricity demand are of central importance to policy makers and utilities for purposes of adequately planning future investments in new generating capacity. Total electricity consumption in California has more than quadrupled since 1960, and the share of residential consumption has grown from 26 percent to 34 percent (EIA 2008). Today, electricity consumption from California's residential sector alone is equivalent to 50 percent of Mexico's total electricity consumption. The majority of electricity in California is provided by three investor-owned utilities and more than a hundred municipal utilities.

On a per capita basis, California's residential consumption has stayed almost constant since the early 1970s, while most other states have experienced rapid growth in per capita consumption. The slowdown in growth of California's per capita consumption roughly coincides with the major energy crisis and imposition of aggressive energy-efficiency and conservation programs during the early 1970s (which, however, took several years to take effect). The average annual growth rate in per capita consumption during 1960–1973 was approximately 7 percent and slowed to a remarkable 0.29 percent during 1974–1995. Growth rates during the last decade of available data have increased to a higher rate of 0.63 percent, and this difference in growth rates is statistically significant. While it is impossible to test what is driving this upswing in a causal sense, rising temperatures and the population expansion in the hot inland areas may be responsible for part of this change in trend—which works against California's aggressive energy-efficiency measures.

California's energy system faces several challenges in attempting to meet future demand (CEC 2005). In addition to rapid population growth, economic growth and an uncertain regulatory environment, the threat of significant global climate change has recently emerged as a major factor influencing the long term-planning of electricity supply. The electric power sector will be affected by climate change through higher cooling demand, lower heating demand, and potentially stringent regulations designed to curb emissions from the sector. The current paper focuses on the San Francisco Bay Area. We make three specific contributions to the literature on simulating the impacts of climate change on residential electricity consumption.

First, through an unprecedented opportunity to access the complete billing data of California's three major investor-owned utilities, we are able to provide empirical estimates of the temperature responsiveness of electricity demand based on micro-data. Second, we allow for a geographically specific response of electricity demand to changes in weather. Third, we provide simulations of future electricity demand under constant and changing climate, electricity price, and population scenarios.

The paper is organized as follows: Section 2 reviews the literature assessing the impacts of climate change on California's electricity demand; Section 3 describes the sources of the data used in this study; Section 4 contains the econometric model and estimation results; Section 5 examines simulations of the impacts of climate change on residential electricity demand; and Section 6 presents the conclusions.

2.0 Literature Review

Historically, the literature forecasting electricity demand has focused on the role of changing technology, prices, incomes, and population growth (e.g., Fisher and Kaysen 1962). Early studies in demand estimation acknowledged the importance of weather in electricity demand and explicitly controlled for it to prevent biased coefficient estimates, as well as gaining estimation efficiency for the remaining parameters (e.g., Houthakker and Taylor 1970). Simulations based on econometrically estimated demand functions had focused on different price, income, and population scenarios while assuming a stationary climate system. The onset of anthropogenic climate change has added a new and important dimension of uncertainty to future demand, which has spawned a small body of academic literature on economic impacts estimation.

The literature on climate change impacts estimation can be divided into two approaches: electricity demand simulation, and a statistics-based econometric approach. In the engineering literature, large-scale bottom-up simulation models are used to simulate future electricity demand under varying climate scenarios. The advantage of the simulation model approach is that it allows one to simulate the effects of climate change given a wide variety of technological and policy responses. The drawback to these models is that they contain a large number of response coefficients and make a large number of assumptions about the evolution of the capital stock for either of which there is little empirical guidance. The earliest impacts papers adopt this simulation approach and suggest that global warming will significantly increase energy consumption.

Cline (1992) provides an early study on the impacts of climate change in his seminal book *The Economics of Global Warming*. His section dealing with the impact on space cooling and heating relies on an earlier report by the U.S. Environmental Protection Agency (1989). That study of the potential impact of climate change on the United States uses a utility planning model developed by Linder et al. (1987) to simulate the impact on electric utilities in the United States and finds that increases in annual temperatures ranging from 1.0°C–1.4°C (1.8°F–2.5°F) in 2010 would result in demand of 9 percent to 19 percent above estimated new capacity requirements (peak load and base load) in the absence of climate change. Estimated impacts rise to 14 percent and 23 percent for the year 2055 and an estimated 3.7°C (6.7°F) temperature increase.

Baxter and Calandri (1992) provide another early study in this literature and focus on California's electricity use, employing a partial equilibrium model of the residential, commercial, agriculture, and water pumping sectors to examine total consumption and peak demand. They project electricity demand for these sectors to the year 2010 under two global warming scenarios: a rise in average annual temperature of 0.6°C (1.1°F) (Low scenario) and of 1.9°C (3.4°F) (High scenario). They found that electricity use increases from the constant climate scenario by 0.6 percent to 2.6 percent, while peak demand increases from the baseline scenario by 1.8 percent to 3.7 percent.

Rosenthal et al. (1995) focus on the impact of global warming on energy expenditures for space heating and cooling in residential and commercial buildings. They estimate that a 1°C (1.8°F) increase in temperature will *reduce* U.S. energy expenditures in 2010 by $5.5 billion (1991 dollars). This reduction is likely due to reduced heating demand.

The economics literature has favored the statistics-based econometric approach to impacts estimation, which is the approach adopted in the current study. While there is much literature on econometric estimation of electricity demand, the literature on climate change impacts estimation is limited and relies on panel estimation of heavily aggregated data or cross-sectional analysis of more micro-level data. Mansur et al. (2008) and Mendelsohn (2003) endogenized fuel choice, which is usually assumed to be exogenous. They find that warming will result in switching towards electricity, due to increased demand for cooling. The drawback of the cross-sectional approach is that one cannot econometrically control for unobservable differences across firms and households, which may be correlated with weather/climate. If that is the case, the coefficients on the weather variables and corresponding impacts estimates may be biased.

Instead of looking at a cross section of firms or households, Franco and Sanstad (2008) explain pure time series variation in hourly electricity load at the grid level over the course of a year. They use data reported by the California Independent System Operator for 2004 and regress it on average daily temperature. The estimates show a nonlinear impact of average temperature on electricity load, and a linear impact of maximum temperature on peak demand. They link the econometric model to climate model output from three different global circulation models (GCMs) forced using three Intergovernmental Panel for Climate Change (IPCC) scenarios (A1Fi, A2, and B1) to simulate the increase in annual electricity and peak load from 2005–2099. Relative to the 1961–1990 base period, the range of increases in electricity and peak load demands are 0.9 to 20.3 percent and 1.0 to 19.3 percent, respectively.

Crowley and Joutz (2003) use a similar approach, where they estimate the impact of temperature on electricity load using hourly data in the Pennsylvania, New Jersey, and Maryland Interconnection. Some key differences, however, are that they control for time-fixed effects and define the temperature variable in terms of heating and cooling degree days. They find that a 2°C (3.6°F) increase in temperature results in an increase in energy consumption of 3.8 percent of actual consumption, which is similar to the impact estimated by Baxter and Calandri (1992).

Deschênes and Greenstone (2007) provide the first panel data–based approach to estimating the impacts of climate change on residential electricity demand. They explain variation in U.S. state-level annual panel data of residential energy consumption at the state-year level, as provided by the U.S. Energy Information Administration's State Energy Data System, using flexible functional forms of daily mean temperatures. The identification strategy behind their paper, which is the one adopted here as well, relies on random fluctuations in weather to identify climate effects on electricity demand. The model includes state fixed effects and census division by year fixed effects, and controls for precipitation, population, and income. The temperature data enter the model as the number of days in 20 predetermined temperature intervals. The authors find a U-shaped response function where energy consumption is higher on colder and hotter days. The impact of climate change on annual energy consumption by 2099 is in the range of 15 to 30 percent of the baseline estimation, or $15 to $35 billion (2006 dollars). The panel data approach allows one to control for differences in unobservables across the units of observation, resulting in consistent estimates of the coefficients on temperature.

The current paper is part of the first project using a panel of household-level electricity billing data to examine the impact of climate change on residential electricity consumption. Through a unique agreement with California's three largest investor-owned utilities, we gained access to the complete billing data for the years 2003–2006. We identify the effect of temperature on electricity demand using within-household variation in temperature, which is made possible through variation in start dates and lengths of household billing periods. Since our data set is a panel, we can control for household fixed effects, month fixed effects, and year fixed effects. The drawback of this data set is that the only other information we have about the household is the price of electricity purchased and the five-digit ZIP code location. The drawback of these data is that we cannot control for time-varying confounders at the household level; for example, income or installed capital. If these are correlated with weather at the household level, conditional on our fixed effects, our parameter estimates will be biased.

3.0 Data

3.1 Residential Billing Data

The University of California Energy Institute, jointly with California's investor-owned utilities, established a confidential data center, which contains the complete billing history for all households serviced by Pacific Gas and Electric, Southern California Edison, and San Diego Gas and Electric for the years 2003–2006. For this project, we received permission to access these data. These three utilities provide electricity to roughly 80 percent of California households.

The data set contains the complete information for each residential customer's bills over the four-year period. Specifically, we observe an identification for the physical location, a service account number,[1] bill start date, bill end date, total electricity consumption in kilowatt-hours (kWh), and the total amount of the bill in U.S. dollars ($) for each billing cycle—as well as the five-digit ZIP code of the premises. Only customers who were individually metered are included in the data set. For the purpose of this paper, a customer is defined as a unique combination of premise and service account number.

It is important to note that each billing cycle does not follow the calendar month, and the length of the billing cycle varies across households, with the vast majority of households being billed on a 25–35 day cycle. While data are available on additional years for some utilities, due to the discrepancy of the availability of billing data from each utility, the study is limited to the years 2003 to 2006, where billing data from all three utilities are avaliable. Hereafter, this data set is referred to as "billing data." Figure 1 displays the ZIP codes for which we have data; these include the majority of the state.

Due to the difference in climate conditions across the state, California is divided into 16 building climate zones, each of which requires different minimun efficiency building standards specified in an energy code. We expect this difference in building standards to lead to a different impact of temperature change on electricity consumption in each zone. We will use this information to separately estimate the impact of mean daily temperature on electricity consumption by climate zone. We assign each household to a climate zone via their five-digit ZIP code through a list, which we obtained from the California Energy Comission. The San Francisco Bay Area counties are split across five of the sixteen climate zones (1, 2, 3, 4 and 12). Figure 1 below maps these five climate zones across five-digit ZIP codes in the Bay Area.

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[1] Premise identification number does not change with the occupant of the residence. Service account number, however, does change with the occupant of the residence.

Figure 1. Bay Area California Energy Commission Building Climate Zones (Shaded) and Weather Station Locations (Pins)

The complete billing data set contains 300 million observations, which exceeds our ability to conduct estimation using standard statistical software. We therefore resort to sampling from the population of residential households to conduct econometric estimation. We designed the following sampling strategy. First, we only sample from households with regular billing cycles, namely 25–35 days in each billing cycle, and those which have at least 35 bills over the period of 2003–2006.[2] We also remove bills with average daily consumption less than 2 kWh or more than 80 kWh, since we are concerned that these outliers are not residential homes, but rather vacation homes and small-scale private manufacturing facilities. Further, our data do not contain single-metered multifamily homes. Our results should be interpreted keeping this in mind.

From the population subject to the restrictions above, we take a random sample from each ZIP code, making sure that the relative sample sizes reflect the relative sizes of the population by ZIP code. We draw the largest possible representative sample from this population given our computational constraints. We proceed with estimation of our models by climate zone, which makes concerns about sampling weights moot. Finally, California has a popular program for

[2] With the regular billing cycle, there should be about 48 bills for the existing households during 2003–2006.

low-income families—California Alternate Rates for Energy (CARE)—where program eligible customers receive a 20 percent discount on electric and natural gas bills. We exclude CARE households from our sample.

No single ZIP code is responsible for more than 0.5 percent of total consumption. Table 1 displays the summary statistics of our consumption sample by climate zone for the Bay Area. There is great variability in average usage across climate zones, with Zone 3's average consumption per bill roughly 65 percent that of the interior Zone 12. The average electricity price is almost identical across zones, at 13 cents per kWh.

Table 1. Summary Statistics for Non-CARE Households

			Usage per Bill per Billing Cycle (kWh)		Average Price per Billing Cycle ($/kWh)		Percentiles Daily Mean Temperature Distribution in Sample (°F)				
Zone	**No. of Obs.**	**No. of HH**	**mean**	**s.d.**	**mean**	**s.d**	**1**	**5**	**50**	**95**	**99**
1	1,459,578	31,879	550	354	0.13	0.03	34.5	37.5	54.7	77.0	80.0
2	2,999,408	65,539	612	385	0.13	0.03	36.0	39.0	55.5	77.5	80.5
3	3,200,851	69,875	469	307	0.13	0.02	42.0	44.3	57.0	75.0	78.0
4	4,232,465	92,294	605	362	0.13	0.03	40.5	42.8	57.8	81.4	85.5
12	3,123,404	68,342	721	420	0.13	0.03	38.5	40.8	58.5	84.0	87.0

Note: The table displays summary statistics for residential electricity consumption for the sample used in estimation of the weather response functions and includes households in non-Bay Area counties.

3.2 Weather Data

To generate daily weather observations to be matched with the household electricity consumption data, we use the Cooperative Station Dataset published by National Oceanic and Atmospheric Administration's (NOAA's) National Climate Data Center (NCDC). The data set contains daily observations from more than 20,000 cooperative weather stations in the United States, U.S. Caribbean Islands, U.S. Pacific Islands, and Puerto Rico. Data coverage varies by station. Since our electricity data cover the State of California for the years 2003–2006, the data set contains 370 weather stations reporting daily data. In the data set we observe daily minimum and maximum temperatures, as well as total daily precipitation and snowfall. Since the closest meaningful geographic identifier of our households is the five-digit postal ZIP code, we select stations as follows. First, we exclude any stations not reporting data in all years. Further, we exclude stations reporting fewer than 300 observations in any single year and stations at elevations more than 7000 feet above sea level, which leaves us with 274 "valid" weather stations for the state.[3] Figure 1 displays the distribution of the subset of weather stations in the Bay Area as red pins. While there is good geographic coverage of weather stations for our sample, we do not have a weather station reporting data for each ZIP code. To assign a daily value for temperature and rainfall, we need to assign a weather station to each ZIP code. We calculate the Vincenty distance[4] of a ZIP code's centroid to all valid weather stations and assign the closest weather station to that ZIP code. As a consequence of this procedure, each weather station on average provides data for approximately 10 ZIP codes.

Since we do not observe daily electricity consumption by household, but rather monthly bills for billing periods of differing length, we require a complete set of daily weather observations. The NCDC data have a number of missing values, which we fill in using the following algorithm. If a station is missing values for minimum/maximum temperature or precipitation, we regress the weather outcome of interest on the same variable for the 10 closest stations each reporting data for at least 200 days a year. We then use the predicted value from this regression to fill in the missing observation. If there still are missing values, due to incomplete time series from the 10 neighboring stations, we regress the series on the nine closest stations and use the predicted values. We repeat this process until all missing values for the station are filled. We end up with a complete set of time series for minimum temperature, maximum temperature, and precipitation for the 274 weather stations in our sample. To ensure that we are not fabricating bad-quality data, we set aside 10 percent of the observed data and pretend that these observations are missing. We run our algorithm on these artificially incomplete series. When regressing the resulting series for temperature on the actual series, the intercept of the regression is indistinguishable from zero, and the slope coefficient is indistinguishable from 1. The correlation coefficient for the two series is 0.99. For the remainder of our empirical analysis, we use these patched series as our observations of weather.[5]

3.3 Other Data

In addition to quantity consumed and average bill amount, all we know about the households is the five-digit ZIP code in which they are located. We purchased socio-demographics at the ZIP code level from a firm aggregating this information from census estimates (zip-codes.com).[6] We only observe these data for a single year: 2006. The variables we will make use of are total population and average household income.

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[3] The cutoff of 300 valid days is arbitrary. If we limit the set of weather stations to those providing a complete record, we would lose roughly half of all stations. We conducted robustness checks using different cutoff numbers, and the estimation results are robust.

[4] The Vincenty distance takes into account the Earth's curvature when calculating distances between two points.

[5] Inverse distance weighting provides an alternative approach to filling in missing temperature values, which, given the good fit of our algorithm, we have not explored further in this report.

[6] We simply match these variables to the five-digit ZIP code. For details on how these variables are constructed, please consult the vendor's website (www.zip-codes.com).

4.0 Econometric Estimation

As discussed in the previous section, we observed each household's monthly electricity bill for the period 2003–2006. Equation 1 below shows our main estimating equation. It is a simple log-linear demand equation, which has commonly been employed in aggregate electricity demand estimation and climate change impacts estimation (e.g., Deschênes and Greenstone 2007):

$$\ln(q_{it}) = \sum_{p=1}^{k} \beta_p D_{pit} + \gamma Z_{it} + \alpha_i + \phi_m + \varphi_y + \varepsilon_{it} \quad , \tag{1}$$

where $\ln(q_{it})$ is the natural logarithm of household *i*'s electricity consumed in kilowatt-hours during billing period *t*. D_{pit} are our measures of temperature, which we discuss in detail below. Z_{it} are observed confounders at the household level, α_i are time-invariant household fixed effects, ϕ_m are month-of-year fixed effects and φ_y are year fixed effects. For estimation purposes our unit of observation is a unique combination of premise and service account number, which is associated with an individual *and* structure. We thereby avoid the issue of having individuals moving to different structures with more- or less-efficient capital or residents with different preferences over electricity consumption moving in and out of a given structure.

California's housing stock varies greatly in its energy efficiency and installed energy-consuming capital. We estimate Equation 1 separately for each of the four climate zones, which cover the Bay Area and are displayed in Figure 1. The motivation for doing so is that we would expect the relationship between consumption and temperature to vary across these zones, as there is a stronger tendency to heat in the more northern and higher-altitude zones and a stronger tendency to cool (but little heating happening) in the hotter interior zones of California.

The main variables of interest in this paper are those measuring temperature. Following recent trends in the literature, we include our temperature variables in a way that imposes a minimal number of functional form restrictions in order to capture potentially important nonlinearities of the outcome of interest—electricity consumption—in weather (e.g., Schlenker and Roberts 2006; Deschênes and Greenstone 2007). We achieve this by sorting each day's mean temperature experienced by household *i* into one of *k* temperature bins.[7] The last five columns of Table 1 display the median, first, fifth, ninetieth, and ninety-fifth percentile of the mean daily temperature distribution by climate zone. To define a set of temperature bins, we split each of the sixteen zones' temperature distributions into a set of percentiles and use those as the bins used for sorting.

For each household and billing period we then counted the number of days the mean daily temperature falls into each bin and recorded this as D_{pit}. The main coefficients of interest to the

[7] We use mean daily temperature as our temperature measure. This allows a flexible functional form in a single variable. An alternative strategy we will explore in future work is separating the temperature variables into minimum and maximum temperature, which are highly correlated with our mean temperature measure.

later simulation exercise are the β_p s, which measure the impact of one more day with a mean temperature falling into bin p on the log of household electricity consumption. For small values, β_p 's interpretation is approximately the percentage increase in household electricity consumption due to experiencing one additional day in that temperature bin.

Z_{it} is a vector of observable confounding variables, which vary across billing periods and households. The first of two major confounders we observe at the household level is the average electricity price for each household for a given billing period. California utilities price residential electricity on a block rate structure. The average price experienced by each household in a given period is therefore not exogenous, since marginal price depends on consumption (q_{it}). Identifying the price elasticity of demand in this setting is problematic, and various approaches have been proposed (e.g., Hanemann 1984; Reiss and White 2005). The maximum-likelihood approaches are computationally intensive, and given our sample size cannot be feasibly implemented here. More important, however, we do not observe other important characteristics of households (e.g., income) that would allow us to provide credible estimates of these elasticities. For later simulation we will rely on the income-specific price elasticities provided by Reiss and White (2005), who used a smaller sample of more-detailed data based on the national-level Residential Energy Consumption Survey (RECS). We have run our models by including price directly, instrumenting for it using lagged prices, and omitting it from estimation. The estimation results are almost identical for all three approaches, which is reassuring. While one could tell a story that higher temperatures lead to higher consumption and therefore higher marginal prices for some households, this bias seems to be negligible, given our estimation results. In the estimation and simulation results presented in this paper, we omit the average price from our main regression.

The second major time-varying confounder is precipitation in the form of rainfall. We calculate the amount of total rainfall for each of the 274 weather stations, filling in missing values using the same algorithm discussed in the previous section. We control for rainfall using a second-order polynomial in all regressions.

The α_i are household fixed effects, which control for time-invariant unobservables for each household. The ϕ_m are month-specific fixed effects, which control for unobservable shocks to electricity consumption common to all households. The φ_y are year fixed effects which control for yearly shocks common to all households. To credibly identify the effects of temperature on the log of electricity consumption, we require that the residuals conditional on all right-hand-side variables be orthogonal to the temperature variables, which can be expressed as $E[\varepsilon_{it} D_{pit} \mid D_{-pit}, Z_{it}, \alpha_i, \phi_m, \varphi_y] = 0$. Since we control for household fixed effects, identification comes from within-household variation in daily temperature after controlling for shocks common to all households, rainfall, and average prices.

We estimate Equation 1 for each climate zone using a least-squares fitting criterion and a clustered variance covariance matrix. Figure 2 plots the estimated temperature response coefficients for each of the climate zones against the midpoints of the bins for the percentile and equidistant bin approaches. The coefficient estimates are almost identical, which is reassuring. We do not display the confidence intervals around the estimated coefficients. The coefficients are so tightly estimated that for visual appearance, displaying the confidence intervals simply makes the lines appear thick.[8] It is important to note that we do not have data for Sacramento, as Sacramento is served by the Sacramento Municipal Utility District and not one of the utilities in our sample.

From this figure, several results stand out. First, the graphs show tremendous heterogeneity in the shape of the temperature response of electricity demand across climate zones. Zone 1 has an almost flat temperature response function, whereas zones 2, 3, 4, and 12 have increasingly steep temperature response at high temperatures. All zones display a very slight negative slope at lower temperatures, indicating a decreased demand for space heating as temperatures increase. California's households mostly use natural gas for space heating, which explains why for most areas we do not see a steeper negative slope at mild temperatures. This is consistent for a lower share of homes using electricity for heat in California (22 percent) than the national average (30 percent). Further, many of these electric heaters are likely located in areas with very low heating demand, given the high cost of using electricity for heat compared to natural gas. While there is use of electricity for heating directly, a significant share of the increased demand at lower temperatures is likely to stem from the operation of fans for natural gas heaters.

We now turn to simulating electricity demand under different scenarios of climate change using these heterogeneous response functions as the underlying functional form relationship between household electricity consumption and temperature.

[8] The full estimation results for each zone are available from the authors upon request.

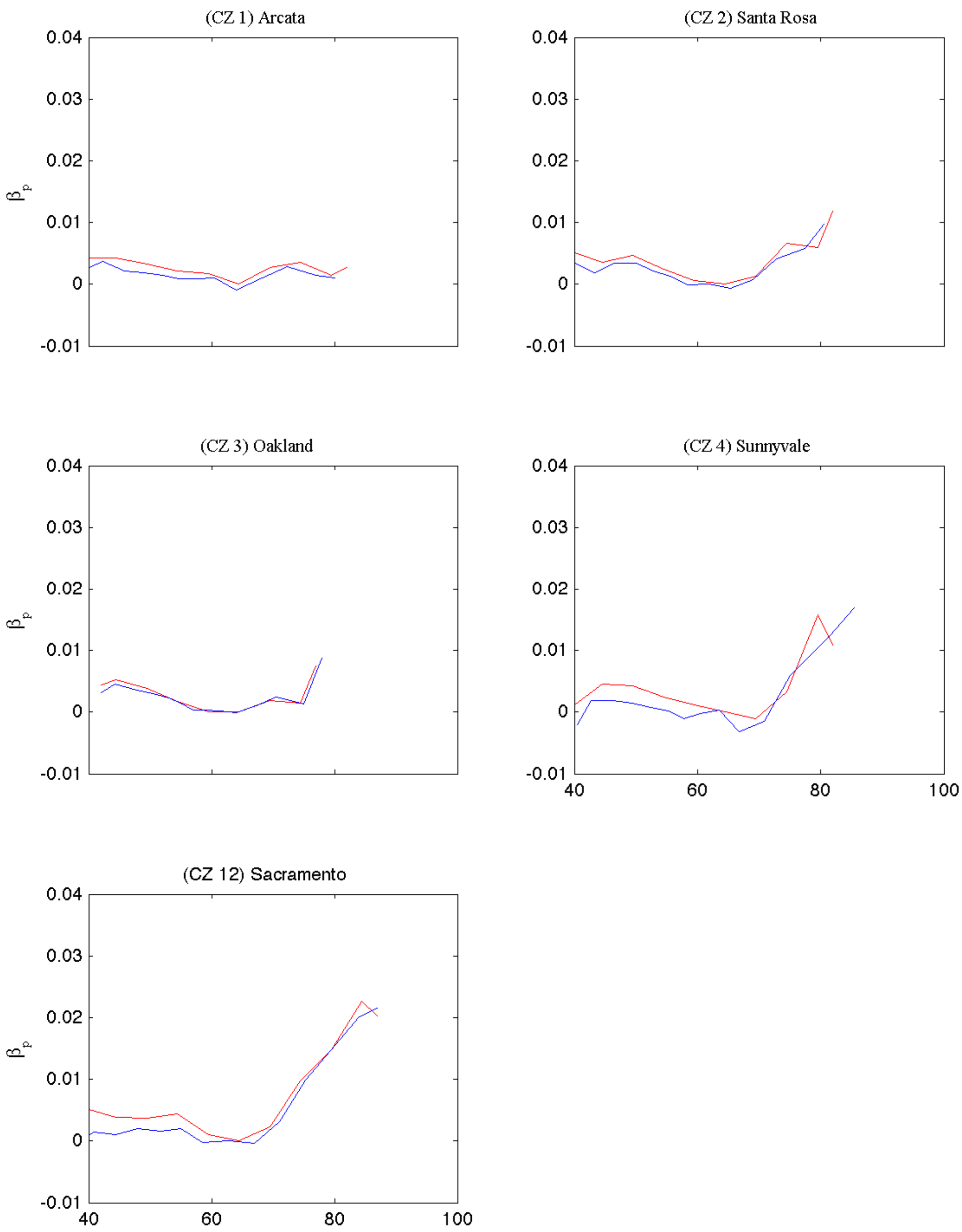

Figure 2. Estimated Climate Response Functions for California Energy Commission Climate Zones 1, 2, 3, 4, and 12. The panels display the estimated temperature slope coefficients for each of the fourteen percentile bins (blue) and the equidistant bins (red) against the midpoint of each bin. The plots were normalized using the coefficient estimate for the 60°F–65°F (16°C–18°C) temperature bin.

5.0 Simulations

In this section we simulate the impacts of climate change on electricity consumption using three different climate models each forced by two different SRES emissions scenarios, three different electricity price scenarios, and three different population growth scenarios. We calculate a trajectory of aggregate electricity consumption from the residential sector until the year 2100, which is standard in the climate change literature. To understand the impact of uncertainty surrounding these three different factors on aggregate demand, we introduce them sequentially.

5.1 Temperature Simulations

To simulate the effect of a changing climate on residential electricity demand, we require estimates of the climate sensitivity of residential electricity demand, as well as a projection of future climate under climate change. The simulation for this section uses the estimated climate response parameters shown in Figure 2. Using these estimates as the basis of our simulation has several strong implications. First, using the estimated β_p parameters implies that the climate responsiveness of demand within climate zones remains constant throughout the century. This is a strong assumption, since we would expect that households in zones which currently do not require cooling equipment may potentially invest in such equipment if the climate becomes warmer. This would lead us to believe that the temperature responsiveness in higher temperature bins would increase over time. On the other hand, one could potentially foresee policy actions such as more stringent appliance standards that improve the energy efficiency of appliances such as air conditioners. This would decrease the electricity per cooling unit required, and shift the temperature response curve downward in the higher buckets.

As is standard in this literature, the future climate is generated by three global circulation models (GCMs). These numerical simulation models generate predictions of past and future climate under different scenarios of atmospheric greenhouse gas concentrations. The quantitative projections of global climate change conducted under the auspices of the IPCC and applied in this study are driven by modeled simulations of two sets of projections of twenty-first century social and economic development around the world, the so-called "A2" and "B1" storylines in the 2000 *Special Report on Emissions Scenarios* (SRES) (IPCC 2000). The SRES study was conducted as part of the IPCC's Third Assessment Report, released in 2001.

The A2 and B1 storylines and their quantitative representations represent two quite different possible trajectories for the world economy, society, and energy system, and imply divergent future anthropogenic emissions, with projected emissions in the A2 being substantially higher. The A2 scenario represents a "differentiated world" with respect to demographics, economic growth, resource use, energy systems, and cultural factors, resulting in continued growth in global carbon dioxide (CO_2) emissions, which reach nearly 30 gigatons of carbon (GtC) annually in the marker scenario by 2100. The B1 scenario can be characterized as a "global sustainability" scenario. Worldwide, environmental protection and quality and human development emerge as key priorities, and there is an increase in international cooperation to address them as well as convergence in other dimensions. A demographic transition results in global population, peaking around mid-century and declining thereafter, reaching roughly 7 billion by 2100. Economic growth rates are higher than those in A2, so that global economic output in 2100 is approximately one-third greater. In the B1 marker scenario, annual emissions reach about 12 GtC in 2040 and decline to about 4 GtC in 2100.

We simulate demand for each scenario using the National Center for Atmospheric Research (NCAR) Parallel Climate Model 1 (PCM), the Geophysical Fluid Dynamics Laboratory 2.1. Climate Model and the Centre National de Recherches Météorologiques Climate Model v3. These models were provided to us in their downscaled version for California using the Constructed Analogues (CA) algorithms (Maurer and Hidalgo 2008). There is no clear guidance in the literature as to which algorithm is preferable for impacts estimation. We therefore provide simulation results using both methods.

To obtain estimates for a percent increase in electricity consumption for the representative household in ZIP code *j* and period *t+h,* we use the following relation:

$$\frac{q_{j,t+h}}{q_{j,t}} = \frac{\exp\left(\sum_{p=1}^{k} \hat{\beta}_{pj} D_{pj,t+h}\right)}{\exp\left(\sum_{p=1}^{k} \hat{\beta}_{pj} D_{pj,t}\right)} \tag{2}$$

We implicitly assume that the year fixed effect and remaining right-hand side variables are the same for period *t+h* and period *t,* which is a standard assumption made in the majority of the impacts literature.

Figure 3 shows the change in the number of days spent in each 5-degree bin of the temperature distribution from 1980–1999 to 2080–2099 using the NCAR PCM forced by scenarios A2 and B1 for San Francisco and Sacramento.[9] A clear upward shift of the temperature distribution is apparent for both locations. For locations with upward-sloping temperature response functions, this entails increases in electricity consumption due to more days spent in higher-temperature bins. Inspecting these graphs for all major urban centers in California, in addition to the two displayed here, confirms what we see in Figure 3. The areas with the steepest response functions at higher-temperature bins happen to be the locations with highest increases in the number of high- and extremely high–temperature days. While this is not surprising, this correspondence leads to very large increases in electricity consumption in areas of the state experiencing the largest increases in temperature, which also happen to be the most temperature sensitive in demand—essentially the southeastern parts of the State of California and the Central Valley, not the Bay Area.

[9] We use Sacramento here purely to demonstrate the difference in projected changes in climate for coastal versus interior parts of the "Bay Area." As discussed earlier, we do not simulate impacts for the Sacramento region.

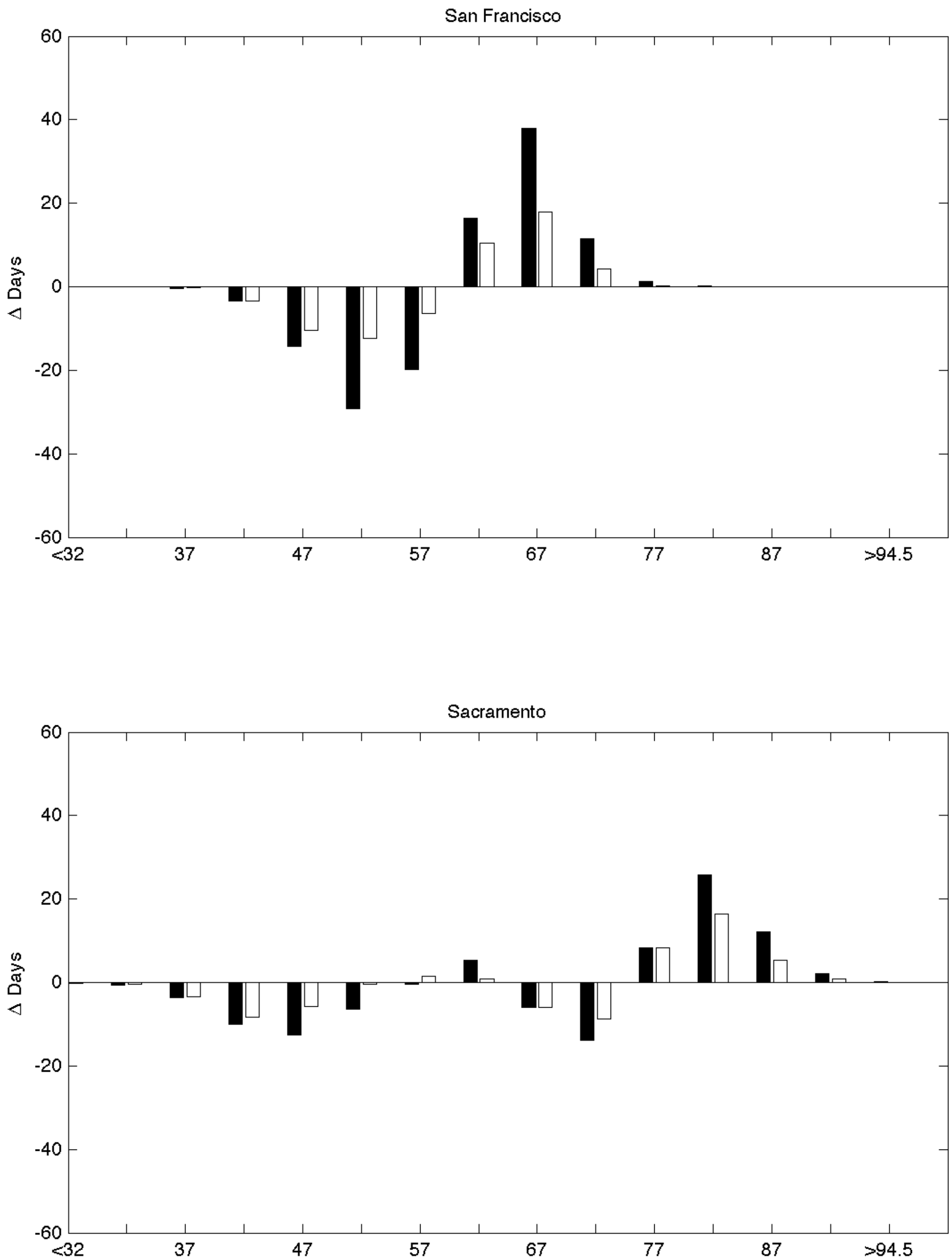

Figure 3. Change in Number of Days in Each 5-degree Temperature Bin for 2080–2099 Relative to 1980–1999 for San Francisco and Sacramento under the IPCC SRES Scenario A2 (Black) and B1 (White) Using the NCAR PCM with the Constructed Analogues Downscaling Method

The first simulation of interest generates counterfactuals using the same unit of observation used in estimation, which is the percent increase in residential electricity consumption by a representative household in each ZIP code. We feed each of the two climate model scenarios through Equation 2 using the 1961–1990 average number of days in each temperature bin as the baseline. Figure 4 displays the predicted percent increase in per-household consumption for the period 2080–2099 using the GFDLv3 model forced by the B1 scenario using the percentile bins. Figure 5 displays the simulation results for the SRES forcing scenario A2.

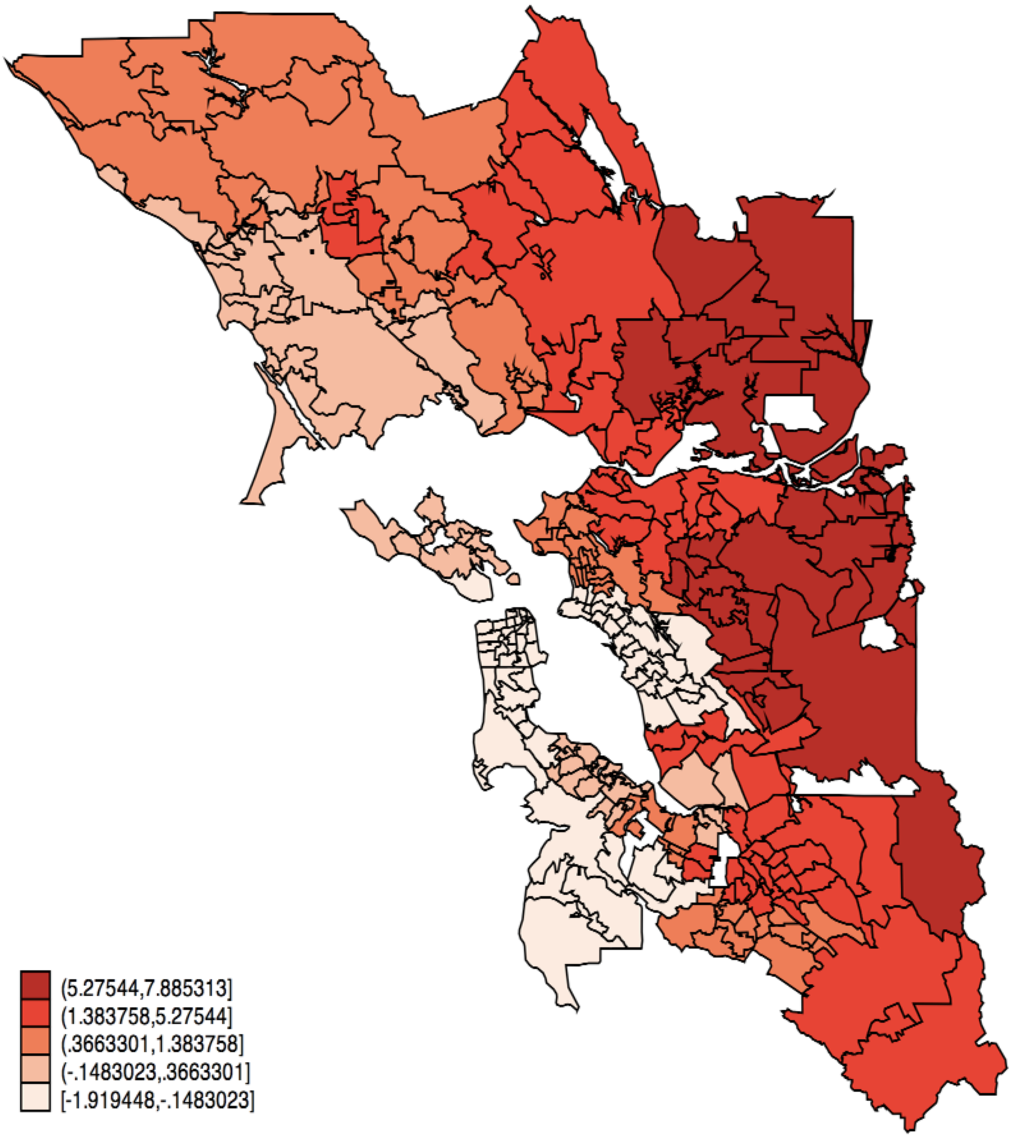

Figure 4. B1 Scenario: Simulated Percentage Increase in Household Electricity Consumption by ZIP Code for 2080–2099 over 1961–1990

The Model GFDLv3 was forced by IPCC SRES B1. White areas are either outside of the study area or indicate that ZIP code billing data were not available.

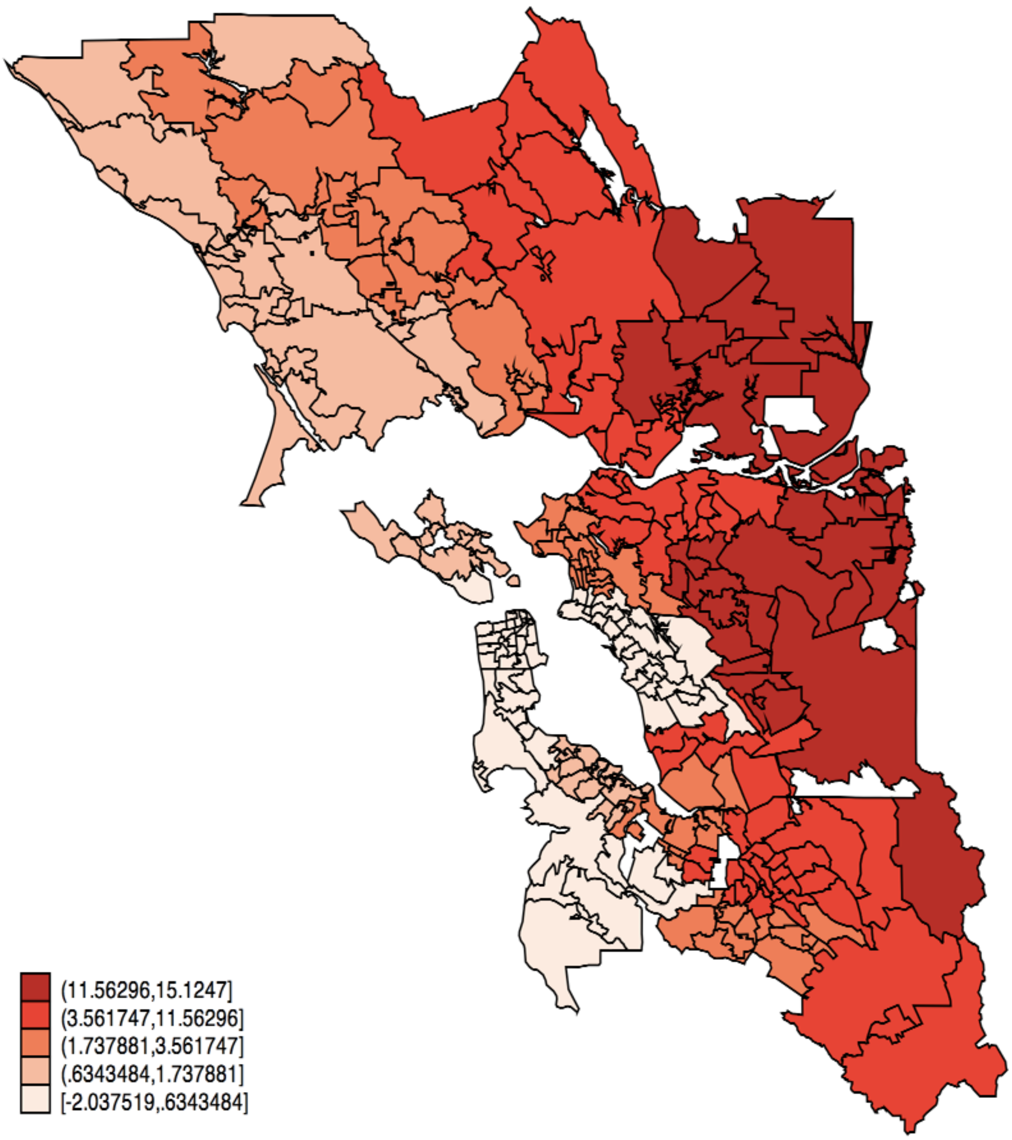

Figure 5. A2 Scenario: Simulated Percentage Increase in Household Electricity Consumption by ZIP Code for 2080–2099 over 1961–1990
The Model GFDLv3 was forced by IPCC SRES A2.

Changes in per-household consumption are driven by two factors: the shape of the weather-consumption relationship and the change in projected climate relative to the 1961–1990 period. The maps show that for areas closer to the coast in the Bay Area (San Francisco, Marin, Oakland, and much of the peninsula), electricity demand at the household level will increase little by the end of the century. The increases are largest for the interior areas (e.g., Contra Costa County). Some ZIP codes are expected to see drops in household-level electricity consumption—even at the end of the current century.

It is important to keep in mind that the current projections assume no change in the temperature electricity response curve. Specifically, the current simulation rules out an increased penetration of air conditioners in areas with currently low penetration rates (e.g., San Francisco) or improvements in the efficiency of these devices. The projected drops essentially stem from slightly reduced heating demand. The simulation results displayed in Figure 5, which are the household increases in energy demand by ZIP code for the higher-emissions scenario A2, show almost identical spatial patterns, yet larger overall increases in demand.

While changes in per capita demand are interesting, from a capacity planning perspective it is overall demand that is of central interest from this simulation. We use the projected percent increase in household consumption by Bay Area ZIP code and calculate the weighted overall average increase, using the number of households by ZIP code as weights, in order to arrive at an aggregate percent increase in demand. The first two columns of Table 2 display these simulation results for aggregate demand. Predicted aggregate demand across all ZIP codes in our Bay Area data set for the currently more realistic emission scenario A2 range from a 1.06 percent increase in total demand to a 4.05 percent increase in total demand by the end of the century depending on the climate model employed.

Table 2. Simulated Percent Increase in Total Bay Area Residential Electricity Consumption Relative to 1961–1990 for the Constant, Low-Price, and High-Price Scenarios

Year	Price Increase Over 2000 (%)	A2			B1		
		CNRM (%)	GFDL (%)	NCAR PCM (%)	CNRM (%)	GFDL (%)	NCAR PCM (%)
2000-2019	+0	0.15	0.12	0.06	0.03	0.15	-0.07
2020-2039	+0	0.22	0.74	0.02	0.21	0.37	0.05
2040-2059	+0	0.48	1.01	0.25	0.38	0.63	0.18
2060-2079	+0	1.20	1.98	0.56	0.51	0.98	0.17
2080-2099	+0	2.59	4.05	1.06	0.65	1.33	0.29
2000-2019	+0	0.15	0.12	0.06	0.03	0.15	-0.07
2020-2039	+30	-9.45	-8.99	-9.64	-9.46	-9.31	-9.61
2040-2059	+30	-9.22	-8.74	-9.42	-9.31	-9.08	-9.49
2060-2079	+30	-8.56	-7.86	-9.15	-9.19	-8.76	-9.49
2080-2099	+30	-7.31	-5.99	-8.70	-9.06	-8.45	-9.39
2000-2019	+0	0.15	0.12	0.06	0.03	0.15	-0.07
2020-2039	+30	-9.45	-8.99	-9.64	-9.46	-9.31	-9.61
2040-2059	+60	-18.92	-18.48	-19.10	-19.00	-18.79	-19.16
2060-2079	+60	-18.33	-17.70	-18.85	-18.89	-18.50	-19.16
2080-2099	+60	-17.20	-16.02	-18.45	-18.78	-18.22	-19.06

Note: All results use the 14 percentile temperature binning approach and the Constructed Analogues Downscaling Approach.

5.2 Temperature and Price Simulations

The assumed flat prices from the previous section can be considered a benchmark for comparison. It is meaningful and informative to essentially imagine climate change imposed on today's conditions. It is worth pointing out, however, that real residential electricity prices in California have been, on average, flat since the early-mid 1970s spike. In this section we will relax the assumption of constant prices and provide simulation results for increasing electricity prices under a changing climate. These results have been graciously provided by Sanstad, Johnson, Goldstein, and Franco (2009).

While no guidance can reveal what will happen to electricity prices 20 years or further out into the future, we construct two scenarios. The first scenario we consider is a discrete 30 percent increase in real prices starting in 2020 and remaining at that level for the remainder of the century. This scenario is based upon current estimates of the average statewide electricity rate impact by 2020 of AB 32[10] compliance, combined with natural gas prices, on generators within the electric power sector. These estimates are based on an analysis commissioned by the California Public Utilities Commission. This scenario represents the minimum to which California is committed in the realm of electricity rates. It could be interpreted as one that assumes very optimistic technological developments post 2030, implying that radical CO_2 reduction does not entail any cost increases.

The second scenario we consider is one where electricity prices increase by 30 percent in 2020 and another 30 percent in 2040 and remain at that level thereafter. We consider the additional price increase in mid-century as, in essence, an "increasing marginal cost" story. Under this scenario, AB 32 is successfully implemented and a path toward achieving the 2050 targets is put in place. These additional steps are assumed to be proportionally more expensive.

To simulate the effects of price changes on electricity demand, we require good estimates of the price elasticity of demand. This paper relies on the estimates of mean price elasticity provided by Reiss and White (2005). Specifically, they provide a set of average price elasticities for different income groups, which are adopted here. Since we do not observe household income, we assign a value of price elasticity to each ZIP code based on the average household income for that ZIP code. Households are separated into four buckets, delineated by $18,000, $37,000, and $60,000, with estimated price elasticities of -0.49, -0.34, -0.37, and -0.29, respectively. It is important to note that these price elasticities are short-run price elasticities. These are valid if one assumes a sudden increase in prices, as we do in this paper. To our knowledge, reliable long-term price elasticities based on micro-data for California are not available, but in theory they are larger than the elasticities used in this paper. These larger elasticities would make prices more effective and lead us to underestimate drops in electricity consumption due to higher prices.

Rows 6–10 in Table 2 present the simulation results under the two different scenarios of climate change given a persistent and sudden increase in electricity prices in the year 2020. Given the range of price elasticity estimates, it is not surprising that the simulated increases in residential electricity demand for the first period after the price increase are roughly 10 percent lower than

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[10] California Global Warming Solutions Act of 2006 [Assembly Bill 32 (Nuñez), Chapter 488, Statutes of 2006].

the predicted increases given constant prices. The path of electricity consumption under these price scenarios returns to levels 8.45–9.39 percent below the 1961–1990 reference period for the period 2080–2099 given the optimistic B2 emissions scenario.

The last five rows in Table 2 present the simulation results for the high-price scenario. Given the significant increase in prices after 2020 and again in 2040, the consumption trajectory decreases by another 10 percent by the end of the century, bringing aggregate consumption significantly below the baseline level. For the optimistic B2 SRES scenario, this results in a drop between 18.22 and 19.06 percent.

5.3 Temperature and Population

California has experienced an almost seven-fold increase in its population since 1929 (BEA 2008). California's population growth rate over that period (2.45 percent) was more than double that of the national average (1.17 percent). Over the past 50 years California's population has grown by 22 million people to almost 37 million in 2007 (BEA 2008). To predict what the trajectory of California's population will look like until the year 2100, many factors have to be taken into account. The four key components driving future population are net international migration, net domestic migration, mortality rates, and fertility rates. The State of California provides forecasts 55 years into the future, which is problematic since we are interested in simulating end-of-century electricity consumption. The Public Policy Institute of California has generated a set of population projections until 2100 at the county level, and we obtained these from Sanstad, Johnson, Goldstein and Franco (2009).

The three sets of projections developed for California and its counties are designed to provide a subjective assessment of the uncertainty of the state's future population. The projections present three very different demographic futures. In the low series, population growth slows as birth rates decline, migration out of the state accelerates, and mortality rates show little improvement. In the high series, population growth accelerates as birth rates increase, migration increases, and mortality declines. The middle series, consistent with (but not identical to) the California Department of Finance projections, assumes future growth in California will be similar to patterns observed over the state's recent history, patterns that include a moderation of previous growth rates but still large absolute changes in the state's population. In the middle series, international migration flows to California remain strong to mid-century and then subside, net domestic migration remains negative but of small magnitude, fertility levels (as measured by total fertility rates) decline slightly, and age-specific mortality rates continue to improve. The high projection is equivalent to an overall growth rate of 1.47 percent per year and results in a quadrupling of population to 148 million by the end of the century. The middle series results in a 0.88 percent annual growth rate and 2.3-fold increase in total population. The low series is equivalent to a 0.18 percent growth rate and results in a population 18 percent higher than today's. Projections are available at the county level and not at the ZIP code level. We therefore assume that each ZIP code in the same county experiences an identical growth rate.

Table 3 displays the simulated aggregate electricity demand given the three population growth scenarios under climate change. This table holds prices constant at the current level and therefore presents a "worst case scenario." It is not surprising to see that population uncertainty has much larger consequences for simulated total electricity consumption compared to climate uncertainty or price uncertainty. The simulations for the low forcing scenario B1 and the low population growth scenario show an 8 percent decrease in consumption, which is due to projected decreases in Bay Area population. The same figure for the medium-growth scenario predicts a 97–99 percent increase in demand for the B1 scenario and 99–105 percent increase for the A2 scenario. The worst-case high population growth scenario predicts a 205–219 percent increase in consumption. This, unsurprisingly, stresses that population trajectories are much bigger drivers of residential electricity demand than climate change.

Table 3. Simulated Percent Increase in Residential Electricity Consumption Relative to 1961–1990 for the Low, Middle, and High Population Scenarios

Period	Population Growth	A2			B1		
		CNRM (%)	GFDL (%)	NCAR PCM (%)	CNRM (%)	GFDL (%)	NCAR PCM (%)
2000-2019	Low	7	7	7	7	7	7
2020-2039	Low	10	11	10	10	10	10
2040-2059	Low	4	5	4	4	4	4
2060-2079	Low	-5	-4	-5	-5	-5	-6
2080-2099	Low	-5	-4	-7	-8	-7	-8
2000-2019	Medium	7	7	7	7	7	7
2020-2039	Medium	24	25	24	24	25	24
2040-2059	Medium	48	49	47	47	48	47
2060-2079	Medium	74	75	72	72	73	71
2080-2099	Medium	102	105	99	98	99	97
2000-2019	High	13	13	13	13	13	13
2020-2039	High	45	46	45	45	45	45
2040-2059	High	84	85	83	83	84	83
2060-2079	High	132	134	131	130	132	130
2080-2099	High	214	219	208	207	209	205

5.4 Temperature, Population, and Prices

Tables 2 and 3 separately show the impacts of the prices and population growth on residential electricity consumption in a world of simulated climate change. It is instructive to show a combined scenario of higher prices *and* population. Table 4 does just that by combining the medium population growth and double price increase scenarios.

Table 4. Simulated Percent Increase in Residential Electricity Consumption in the Bay Area Relative to 1961–1990 for the Middle Population Scenario Under a Two-Time 30% Increase in Prices

Period	A2			B1		
	CNRM (%)	GFDL (%)	NCAR PCM (%)	CNRM (%)	GFDL (%)	NCAR PCM (%)
2000-2019	7	7	7	7	7	7
2020-2039	12	13	12	12	13	12
2040-2059	19	20	19	19	19	19
2060-2079	40	41	39	39	40	38
2080-2099	63	66	60	59	61	59

It is not surprising, given the magnitude of projected population growth, that even under the high-price scenario combined with the medium population growth scenario, the population of the Bay Area has a much larger impact on electricity consumption than does climate change. This, of course, is true for the state as a whole as well.

6. Conclusions

This study provides estimates of the Bay Area counties' aggregate and household-level residential electricity demand under climate change based on a large set of panel micro-data. We use random and therefore exogenous weather shocks to identify the effect of weather on household electricity demand. We link climate zone–specific weather response functions to a state-of-the art downscaled global circulation model to simulate growth in aggregate electricity demand. We further incorporate potentially higher prices and population levels to provide estimates of the relative sensitivity of aggregate demand to changes in these factors.

There are two novel findings from this paper. First, temperature response varies greatly across the climate zones in the Bay Area—from flat to hockey stick shaped. This suggests that aggregating data over the entire Bay Area may ignore important heterogeneity. Second, uncertainty about population, rather than uncertainty about climate change, leads to the greatest uncertainty regarding future demand.

Of course, what is missing from this study is a serious examination of adaptation. Higher temperatures will likely lead households to purchase additional air conditioners. This extensive margin adjustment is not modeled in the current paper, but Auffhammer (2012) uses a two-stage model to study the effects of both intensive and extensive margin adjustments, which will lead to higher climate impacts than those shown in this paper. The other factor, which we simply cannot model, is the impact of the emergence and installation of increasingly efficient air conditioners in response to more-stringent energy-efficiency standards and/or higher prices. As the current paper and its companion pieces should not be interpreted as forecasts, but rather as scenarios that do not account for potential efficiency gains, these studies underline the need for such efficiency measures if there is to be any hope of reducing residential electricity consumption to meet California's greenhouse gas emission–reduction goals.

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